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SCD-MVA: A mobile application for conducting single-case experimental design research during the pandemic

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Abstract

The COVID-19 outbreak emphasizes the need for alternative methods for data gathering and collaboration among researchers in a virtual research environment. One experimental design that is well suited in a social distancing research context is the single-case experimental design (SCD). SCDs can handle disruptions as (a) they do not require large groups gathering for data collection or intervention administration, (b) interventions are administered individually and in some cases remotely, (c) no comparison group is needed, and (d) they are adaptive and flexible designs. The purpose of this article is to introduce the mobile application, SCD-MVA (2019), developed to assists in the design of an SCD, data gathering, data analysis, and remote collaboration. The application allows data management and data sharing among researchers, provides an in real time visualization of the gathered data, stimulates interaction between researchers in terms of designing the SCD, gathering the data, and analyzing the gathered data, and does all these things with no need for in-person meetings of the research team.

KEYWORDS

masked visual analysis, multiple baseline design, "SCD-MVA" mobile application, single-case experimental design

The outbreak of COVID-19 (an infectious disease caused by Severe Acute Respiratory Syndrome Coronavirus 2, SARS-COV-2) has an impact on every aspect of human life (Center for Disease Control, World Health Organization, and United Nations). In a response to stabilize and decrease the number of infections, governments have enforced social distancing, self-isolation (i.e., quarantine), border shutdowns, and travel restrictions. These restrictive measures caused a reduced workforce (and many jobs are lost) across industries (Nicola et al., 2020), going from agriculture within the primary sector, manufacturing within the secondary sector, and many service industries within the tertiary section. For instance, educational institutions have closed down, and the demand for agriculture commodities (i.e., crash in demand from hotels and restaurants) and manufactured products dropped. In contrast, the need for medical supplies, food products (due to panic-buying) have significantly increased. It is clear that the COVID-19 outbreak has significant social-economic impacts.

Among the many social-economic impacts within the service industries, Nicola et al. (2020) state that the most significant impact is on the postgraduate research community (i.e., academics). For instance, funding for non-COVID related research projects have been put on hold (e.g., the National Institute of Health shut down non-critical research and several research institutions put research in humanities and social sciences on hold) and scientific conferences have been cancelled. These conferences provide opportunities for dissemination of research and networking. The COVID-19 outbreak has disrupted how and if data can be collected and how research in general can be conducted and continued (especially when in person data gathering is involved). A certain amount of creativity is needed to explore alternative and innovative ways (that are low cost) to continue conducting research during this changing research climate.

In this article, we are going to discuss one particular type of research design, namely single-case experimental designs (SCDs),

which have the flexibility to be adaptive in this changing research climate. Because these designs focus on a relatively small number of participants (often 3 or 4) they do not require the coming together of large groups for data collection or intervention administration. Rather interventions are administered individually and in some cases can be administered remotely, and data collection which often involves direct observation, can be done virtually by making use of video recordings (Asan & Montague, 2014). In addition, because these designs are traditionally adaptive designs, where decisions about how long to collect data is made responsively based on the pattern of emerging data, they are suitable for handling disruptions. Traditionally when the pattern of responding is disrupted by an external factor the data collection within the phase (i.e., the control phase or the intervention phase) continues until a stable pattern is again obtained, so that changes between the phases (i.e., between the control phase and the intervention phase) can be unambiguously interpreted.

The purpose of this article is to introduce a mobile application, SCD-MVA (Bursali, Moeyaert, & Cacciotti, 2020) that assists in the design and conduct of an SCD. The SCD-MVA applicationis free and currently runs on iPhones and iPads. The application and can be downloaded via the Apple App Store. Additional information about the application can be found on https://www.singlecasemva.com/. The SCD-MVA mobile application allows data management and data sharing among team members, provides an in real time visualization of the gathered data, stimulates interaction between team members in terms of setting criteria to infer intervention effectiveness, and can calculate whether the intervention has a statistically significant effect. The application provides all these capabilities with no need for in-person meetings of the research team. All extensive planning when designing an experiment that is traditionally done in person, can be done and captured remotely through the mobile application. In addition, the mobile application allows for easy implementation of a masked visual analysis (MVA) approach (which controls for Type I errors in adaptive designs). This approach has many advantages, such as randomization (Kratochwill & Levin, 2010; Todman & Dugard, 1999) and the prevention of experimenter bias (Hantula, 2019). The MVA approach will be discussed in detail in this article. The mobile application will provide whether there is evidence for a statistically significant intervention effect using a randomization distribution.

This article is composed of two major parts. In Part 1, single-case experiment research is introduced. Part 2 involves the introduction of the mobile application, *SCD-MVA*, together with a step-by-step demonstration of the main capabilities and functionalities of the SCD-MVA application.

1 | PART 1: SINGLE-CASE EXPERIMENTAL RESEARCH

1.1 | Introduction to single-case experimental design

Using single-case experimental designs (SCDs), individualized longitudinal data on a dependent variable can be gathered (Barlow, Nock, & Hersen, 2009; Horner & Odom, 2014; Kazdin, 2011; Ledford & Gast, 2018). One participant is repeatedly measured during a control condition, terminated by the implementation of an intervention. The intervention is causing the condition change and the major interest using SCDs is whether this condition change (i.e., the intervention or the independent variable) causes a change in data on the dependent variable (Kratochwill et al., 2010). This change in data can be reflected by for instance a change in the mean level of response, a change in the general data pattern (e.g., linear trend during the control condition versus quadratic trend during the intervention condition), or change in variability (e.g., stable data during the control condition versus highly variable data during the intervention condition).

The major advantage of using an SCD is that no comparison group is needed. Establishing comparable control and intervention groups is challenging and if this criterion is not met, it is hard to attribute changes in data on the dependent variable due to group membership (control group or treatment group) instead of outside experimental factors (Shadish, Cook, & Campbell, 2002). In SCDs, all participants are repeatedly measured during both the control and the intervention condition (i.e., the participants serve as their own controls). Therefore, if changes between the control and the intervention condition are found, it is more likely that this is due to the intervention instead of outside experimental factors. In addition, the intervention is introduced after the baseline condition and therefore the temporal criterion to deduce causality is met (Kratochwill et al., 2010; Shadish et al., 2002). Thus, if designed well (i.e., controlling for intervention confounders), SCEDs are strong experimental designs that can establish a base to answer causality questions.

In order to design the SCD well, enhance the creditability of using SCD findings and make causal inferences, several criteria of methodological rigor need to be met (Ganz & Ayres, 2018). Lobo, Moeyaert, Cunha, and Babik (2017) conducted a review of quality assessment and identified two components that are central for the design of a methodologically sound SCD, namely replication and randomization.

1.1.1 | Replication

In order to make inferences about the effectiveness of the intervention and generalize conclusions beyond the individual experiment, replication is a crucial design component. Generalized conclusions about intervention effectiveness requires replicating the experiment across participants using the same intervention for the same problematic aspect (i.e., dependent variable, Kennedy, 2005; What Works Clearinghouse, 2020).

1.1.2 | Randomization

The second central SCED component is randomization. Randomization tests are desirable in contexts of small *n* as parametric data assumptions are not required and are applicable even when there are missing data (De, Michiels, Tanious, & De Onghena, 2020). In addition,

randomization tests are particularly valuable for single-case studies because they keep history and maturation effects from increasing the probability of incorrectly concluding the treatment had an effect (i.e., Type I error control does not require assumptions about how the outcome variable would have changed over time in the absence of intervention; Bulté & Onghena, 2009; Edgington, 1980; Edgington & Onghena, 2007; Ferron & Onghena, 1996). Randomization tests allow flexibility in defining the test statistic (such as mean differences, nonoverlap metrics, or multilevel models (Heyvaert & Onghena, 2014, Michiels, Tanious, De, & Onghena, 2020, Tanious, De, & Onghena, 2019).

1.1.3 | Multiple baseline designs

An SCD type in which the two central SCD design components can be implemented (i.e., replication and randomization) is the multiple baseline design (MBD) across participants. In this design type, the experiment is replicated across participants. In addition to replicating the experiment, MBDs stagger the change in conditions (i.e., transition from the baseline to the intervention condition) between participants (Gast, Lloyd, & Ledford, 2018). A change in data on the dependent variable is to be expected solely for the participant exposed to the intervention, whereas data on the dependent variable is expected to remain stable for the other participants that are still in the control condition (i.e., Ferron, Moeyaert, Van den Noortgate, & Beretvas, 2014). Evaluating this is possible when data gathering during the stagger between the participants is sufficiently long. Figure 1 gives a graphical display of an MBD across four participants (i.e., Samantha, Frank, Timothy, and Alejandro). The graphical display in Figure 1 was created using a subset of the data gathered by Byun, Hitchcock, and Ferron (2017). Byun et al. investigated the influence of an intervention (i.e., visual-acoustic biofeedback) on a dependent variable (i.e., percent of correct syllable-level tokens). The orange line connects baseline data points whereas the green line connects intervention data points. The transition from the baseline condition to the intervention condition is indicated by a vertical dotted line. As is clear from Figure 1, all participants have a different baseline length, with Samantha having the shortest baseline and Alejandra to longest baseline. The stagger between the intervention starts for the different participants are long enough to allow the treated participant to respond to intervention while the other participants are still in baseline. For instance, Samantha has eight data points in the stagger. It is clear that the data increased up to 80.00 for Samantha, whereas the other participant's data did not exceed a score of 40.43 (for Timothy). This comparison (i.e., Samantha versus the other three participants) is

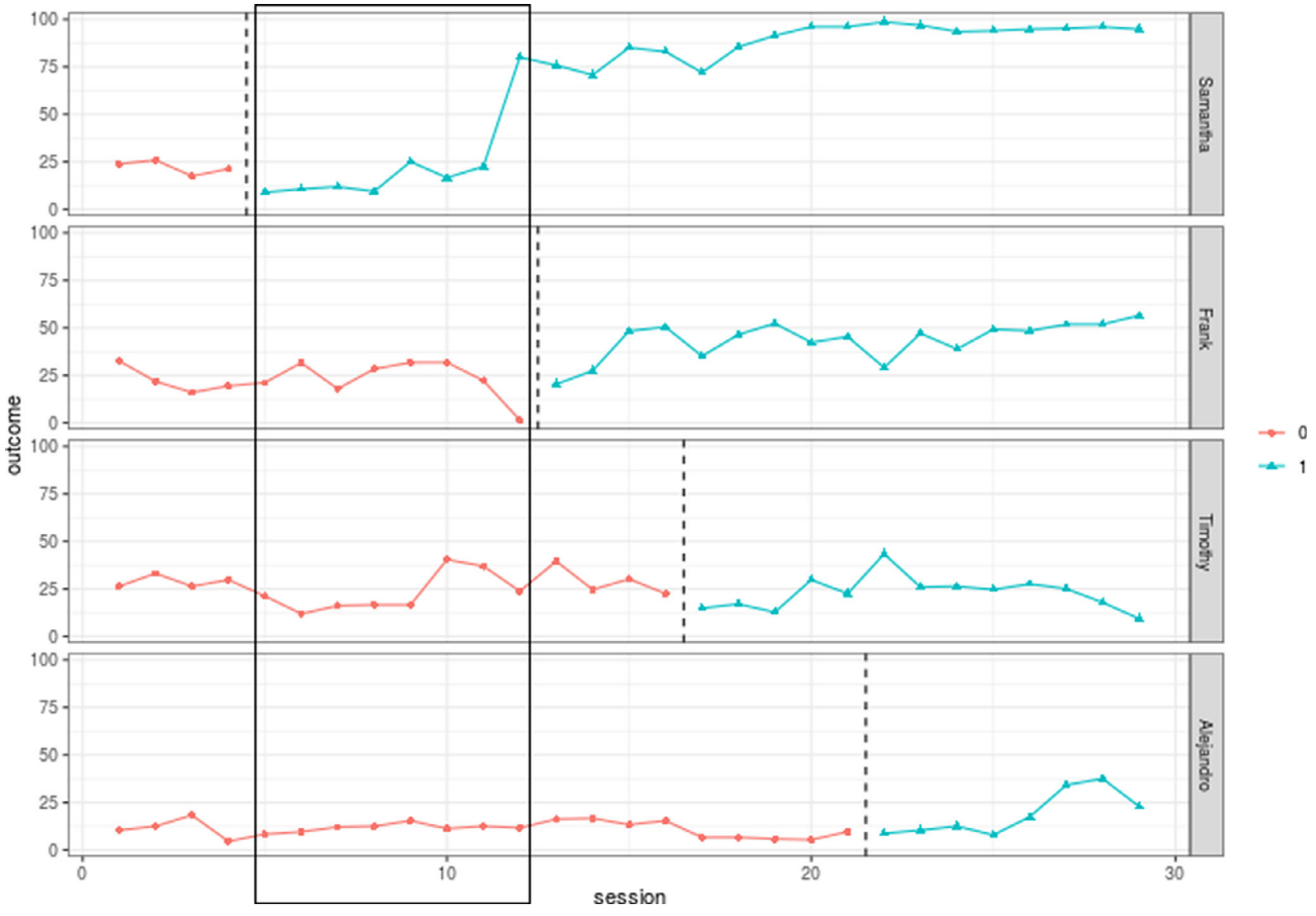


FIGURE 1 Graphical display of a multiple baseline across four participants

indicated with a box in Figure 1. A similar comparison can be done for the other two stagger periods. Because of the replication and staggered change in conditions, MBDs are internally and externally valid, and are the most frequently used SCED type. MBDs will be the focus of this study.

In MBDs, participants can be randomly assigned to baseline lengths (Wampold & Worsham, 1986) and/or interventions start points can be randomly chosen for each participant subject to some constraints (Koehler & Levin, 1998). One of the possible assignments is randomly chosen and this forms the actual MBD experiment. Then the researcher chooses an appropriate test statistic (e.g., mean difference, nonoverlap metric, regression-based effect size, for a detailed overview of statistics, see Manolov & Moeyaert, 2017), collects the data, and calculates the predefined test statistic based on the collected MBD data. Once this is accomplished, the test statistic is calculated for each of the possible alternative random assignments that were recorded at the beginning of the experiment using the collected MBD data. All the test statistic values are sorted and form the randomization distribution. Using this distribution, the statistical significance of the test statistic can be calculated by looking where the obtained test statistic falls within the distribution of possible test statistic values. The *p*-value is calculated as the proportion of possible test statistic values that is as extreme as or even more extreme than the value of the test statistic based on the SCD (Edgington & Onghena, 2007).

1.2 | Designing single-case experiments

Transparency and a priori decisions related to condition transition (i.e., transitioning from control condition to the intervention condition) prevent experimenter bias. Otherwise, the researcher can implement the intervention whenever there is a big drop (or big increase) in data on the dependent variable. This may highly affect the conclusions regarding intervention effectiveness. A priory decisions avoid questionable research practices that can lead to biased results (Hantula, 2019). One way to decide the start of the intervention condition is based on a randomized algorithm. Given the staggered start of the intervention condition in MBDs, the algorithm needs to be restricted as one intervention start point can only be selected once (this avoids that the intervention start at the same time for all the participants). In addition, there needs to be a minimum amount of data gathered during the conditions (i.e., at least three observation is recommended, Kratochwill et al., 2010) and during the stagger (at least one observation). As a consequence, a complete randomized algorithm is not possible.

Another consideration in deciding the moment of condition change is the stability of the control phase. This involves a response-guided approach (Gast, 2014), which is another advantage of using SCDs. This approach allows the researcher to be responsive to the participants' data pattern during the control condition. Instead of choosing fixed condition changes or selecting the condition changes randomly prior to starting the study, the transition from control to experimental condition may be chosen after stable data are obtained. Data stability during the control condition is recommended as intervention effectiveness can be inferred if changes in data on the dependent variable are related to the condition change and not to other factors interfering with the data. For instance, highly variable control data and/or naturally improving data might confound with the intervention. Therefore, stability refers to control data that are not too variable and not trending in the direction of the anticipated change (Barton, Lloyd, Spriggs, & Gast, 2018; Joo, Ferron, Beretvas, Moeyaert, & Van den Noortgate, 2018; Kratochwill, Levin, Horner, & Swodoba, 2014). To avoid experimenter bias, criteria to determine data stability need to be decided a priori. We will demonstrate how the mobile application, SCD-MVA (2019), can be used to establish agreed upon a priori baseline (i.e., control) stability criteria, and accommodate randomization in a manner that ensures phase changes happen only after stability is obtained.

As is clear from the previous paragraphs, several decisions regarding to the design of the single-case experiment need to be made prior to data collection. These decisions involve the minimum number of data measures during the control condition, the intervention condition, and the stagger, the number of experiments (i.e., participants), stability criteria, and a method to evaluate intervention effectiveness (e.g., changes in data pattern and/or changes in variability). In order to enhance transparency, avoid experimenter biases, increase the internal validity and give SCEDs the same credibility compared to group-comparison designs, it is recommended to communicate and share all the decisions related to the design of the experiment with the members of the research team. The SCD-MVA (2019) mobile application, which will be introduced in this article, allows for communication among research members and shares decisions that have been made. These decisions can be accessed at any point in time: before, during and after the experiment. This creates an environment that allows for meaningful discussions between research members (and stimulates critical thinking about selecting suitable criteria and design conditions) and will help in disseminating the experiment to the broader research community. Open communication, transparency, and data sharing are becoming increasingly valuable in the current research climate. Recently, there has been a call in the context of SCD to preregister the planned design and analysis through platforms such as the Open Science Framework (OSF, Johnson & Cook, 2019). The development of the SCD-MVA application responds to this recent call.

1.3 | Analyzing single-case experimental data

Data visualizations can enhance communication between researchers, help in making decisions and help in disseminating the study results. In the field of SCDs, individualized data is traditionally graphically displayed, see Figure 1. Changes in data patterns, and variability in data between the conditions are visually analyzed (based upon predefined criteria) in order to deduce whether there is initial evidence for a causal relation between the introduction of an intervention and a change in data. The SCD-MVA (2019) application that will be

introduced later provides such in real time visualizations of the gathered data (see Figure 2 for an example).

The visual analysis does not result in a summary quantification, which is desirable to communicate study findings (Kratochwill et al., 2014). There is a lack of consensus about which metrics are most appropriate for the quantification (Busse, McGill, & Kennedy, 2015; Manolov & Moeyaert, 2017; Smith, 2012). A result of this is that researchers commonly analyze SCD data using a variety of complementary metrics (i.e., sensitivity analysis, Lobo et al., 2017, Moeyaert, Ferron, Beretvas, & Van den Noortgate, 2014). One unwanted side effect of this is that researchers might only report the results that give evidence in support of the intervention (i.e., selective reporting; Hantula, 2019). In order to prevent this selective reporting and experimenter bias, decisions in terms of the metric of interest need to be made a priori. Criteria to deduce intervention effectiveness needs to be communicated and shared with the research team. Manolov, Moeyaert, and Fingerhut (under review) provide guidance and designed a flowchart helping researchers in this process. The mobile application requires the members of the research study to select a metric prior to the start of the experiment (together with other criteria discussed earlier in the article such as the minimum number of data points per condition).

The MVA approach is a flexible approach combining the advantages of visual analysis, response-guided experimentation (i.e., intervening after the control condition data are stable), randomization (within and across participants), and quantitative analysis. This approach stimulates communication and collaboration among researchers, transparency in a priori decision-making and requires data sharing. MVA requires a research team instead of a single researcher (who is both delivering the data and analyzing the data). This avoids that one researcher solely determines intervention effectiveness and more reliable study results are obtained (i.e., analyst is blinded to the intervention). In addition, the members of the research team communicate and agree upon predefined criteria, which avoids experimenter bias. Using MVA, decisions related to the design and the analysis approach are supported and shared by the research team prior to the start of data collection, as this is inherent in the approach. In the next section, the MVA approach will be introduced, motivating the need of a mobile application enhancing the implementation of MVA in practical settings.

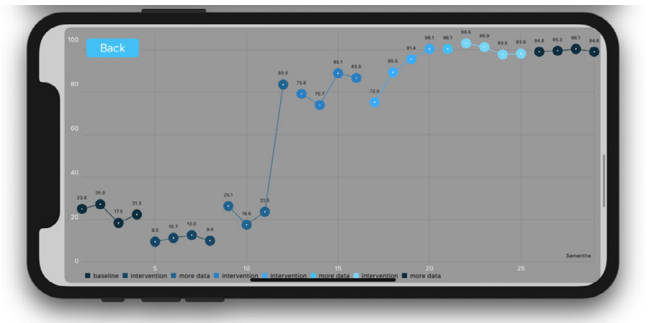


FIGURE 2 Screenshot of the visualizations of the gathered data using the "single case designs: MVA" mobile application

2 | PART 2: MVA APPROACH AND THE SCD-MVA MOBILE APPLICATION

In order to conduct a MVA, the research team needs to be divided in two teams: (1) an intervention team and (2) an analysis team. The role of the intervention team is to collect the data and implement the intervention, and the role of the analysis team is to create and analyze a masked graph. Prior to the start of data gathering, the member(s) of both teams need to communicate, agree and share decisions related to the following factors: the number of participants, the minimum number of data gathered during the baseline and intervention phase, the minimum number of observations in the stagger of the MBD, and set criteria to evaluate data stability, identify outliers and quantify intervention effectiveness. Without agreeing on these factors, the SCD cannot start.

In order to facilitate this process and ensure that objective decisions are made, a user-friendly application, called the SCD-MVA, is developed and will be introduced in this article. To enhance the understanding of the steps involved when conducting an MVA, real data from a published SCED study will be used. The same data will be used to demonstrate the functionality of the SCD-MVA mobile application and to understand how the application facilitates an easy implementation of the approach. The demonstration will also highlight the advantage of using an SCD as the research design and using the application to conduct the experiment (i.e., without the requirement of in-person interaction between research team members).

2.1 | Introduction empirical example

The data that will be used for the empirical demonstration of the MVA approach and the mobile application is retrieved from a published study in the domain of communication disorders. The study was published in 2017 in the Journal of Speech, language, and Hearing Research (Byun et al., 2017). Byun et al. graphically displayed the gathered data. The data retrieval program WebPlotDigitizer 4.3 (Rohatgi, 2020) was used to extract the raw data from this graphical display. WebPlotDigitizer is an open-source, free, valid, and user-friendly data retrieval program (for more information about the data retrieval process, see Moeyaert, Maggin, & Verkuilen, 2015). The Appendix provides an overview of the retrieved data. The data that will be used to explain the MVA approach and demonstrate the application is slightly modified. The reason for this is that the mobile SCD-MVA application does not deal with missing data. In addition, the application does not include postintervention data, so data from the postintervention phase were also excluded. The table in Appendix indicates in color the data points that were maintained.

Byun et al. (2017) investigated an intervention for residual errors effecting/r/. More specifically, the intervention is visual-acoustic

biofeedback and the dependent variable is percent of syllable-level tokens rated correct by blinded listeners. A multiple-baseline design across four participants was used, as the researchers' intention was to demonstrate repeated evidence in support of the intervention (i.e., generalization through replication). In addition, the researchers incorporated randomization (with restriction) as they only allowed the sequence of participants introduced to the intervention to be randomized. The start of the intervention was not randomly decided a priori, as a response-guided approach was chosen. The response-guided approach (instead of a fixed approach) allows researchers to intervene when outcome data are stable (and/or display a pattern in the opposite direction of the anticipated change). This deals with the internal validity threat "maturation" (Shadish et al., 2002). This ensures that changes in outcome patterns are more likely to be attributed to the intervention and not to maturation (or continuation of highly variable data). As there are four participants, there are 4 * 3 * 2 (=24) different randomized assignments possible. The randomization algorithm is standard implemented in the SCD-MVA application for the convenience of the interventionist. After baseline stability criteria are met, the intervention can start for one of the participants. The graphical display of the data from the study of Byun et al. (2017) is presented in Figure 3. In that graph, you can see that the first participant, Alexandro was the last participant to be exposed to the intervention (based on the randomization schedule that was determined prior to the start of the experiment). The graph in Figure 3 was created in RStudio after data retrieval from the original study of Byun et al. (2017).

Other criteria that were decided upon prior to the start of the experiment is a minimum of four baseline observations and four observations during the stagger. If stability was not obtained after eight sessions, then the treatment was initiated for a next randomly chosen participant (nonrespondents are common in the context of this applied study).

2.2 | The MVA approach applied to empirical example

As mentioned in the previous paragraph, criteria need to be chosen to evaluate stability. Byun et al. (2017) specified the stability criterion as: a series of at least four consecutive data points in which the most recent two data points do not demonstrate evidence of improvement or any problematic outliers. Data points deviating more than two standard deviations from the mean across preceding data points are identified as outliers. In addition, evidence for intervention effectiveness was specified a priori. In the study of Byun et al. (2017) the members of the intervention team and analysis team agreed that intervention effectiveness is evidenced by the following two criteria: (1) the mean across sessions in the current phase, excluding the first two data points, is more than 10% points higher than the mean in the preceding phase and (2) data on the dependent measure in the current phase show an upward trend (positive overall slope and final data point is at least 10% points higher than the mean in the preceding phase). Once these criteria are agreed upon, the MVA approach can be started. The

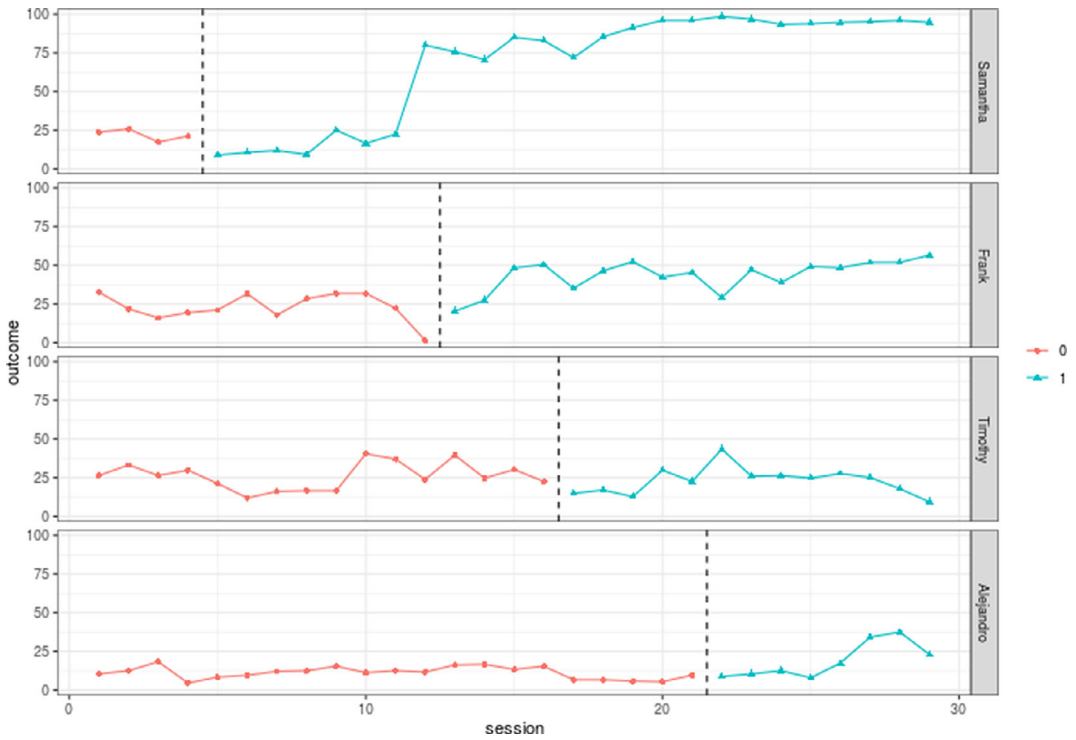


FIGURE 3 Graphical display of data from an MBD across four participants (Byun et al., 2017)

MBD experiment using the MVA approach consists of five phases (i.e., the number of phases equals the number of participants +1) that will be discussed below. One certified speech pathologist was the interventionist and one researcher was part of the analysis team (i.e., both intervention and analysis team consisted of one member, but more team members can be added).

2.2.1 | Subphase 1

The interventionist started by gathering data on syllable-level tokens during four consecutive baseline sessions. After these four sessions, the interventionist uploaded the data to Amazon Mechanical Turk for blinded rating. Once the rating was completed (i.e., the percentage of correct syllable-level tokens per session was determined), the data was sent to the analyst. The analyst downloaded the data and made a graphical display of the data. Figure 4 displays the four outcome measures during the beginning of the control phase for the four participants. Based on the stability criteria decided a priori, the analyst decided that no extra data points were needed and informed the interventionist that the intervention could start for the first randomly determined participant.

2.2.2 | Subphase 2

The interventionist started the intervention for one participant (based on the a priori randomization sequence) and gathered four measures during this intervention phase. Simultaneously four observations were obtained for the remaining three participants that were still in the baseline phase. Changes in the percentage of syllable correct are expected for one participant, whereas no changes are expected for the other participants. Figure 5 displays the data obtained during Subphases 1 and 2 for the four participants (where the second subphase is the beginning of the intervention phase for one participant and a continuation of the baseline phase for the other three participants). No clear changes were obvious, so extra data points were requested by the analyst. It was not until the eighth session during Subphase 2 that a clear change in outcome was obvious, namely for Samantha, see Figure 6. Therefore, after the eighth session, the analyst informed the intervention team that the intervention could be started for the second participant.

2.2.3 | Subphase 3

The interventionist started the intervention for a second participant and gathered four measures during this subphase in which two participants were in intervention and two remained in baseline. Changes in the percentage of syllable correct are expected for one participant, whereas no changes are expected for the other participants. Figure 7 displays the data obtained during Subphases 1, 2, and 3 for the four participants. Clear changes were obvious, namely for Frank, so no extra data points were requested by the analyst. The analyst informed the intervention team that the intervention could be started for the third participant.

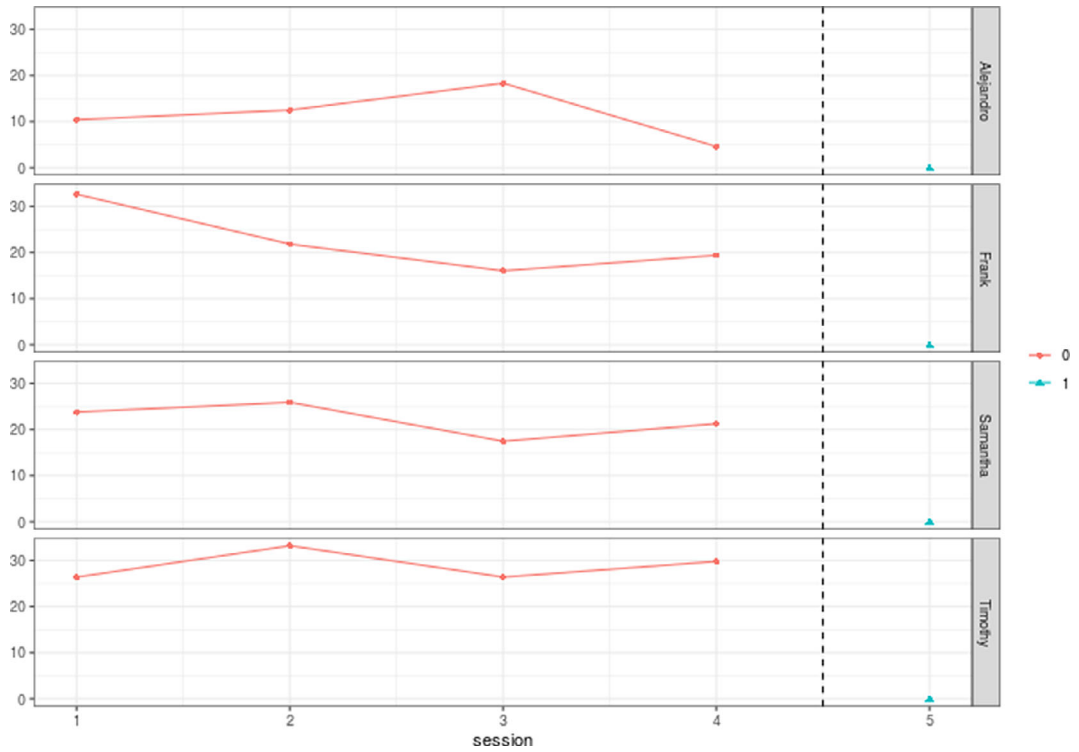


FIGURE 4 Graphical display of Subphase 1 Data

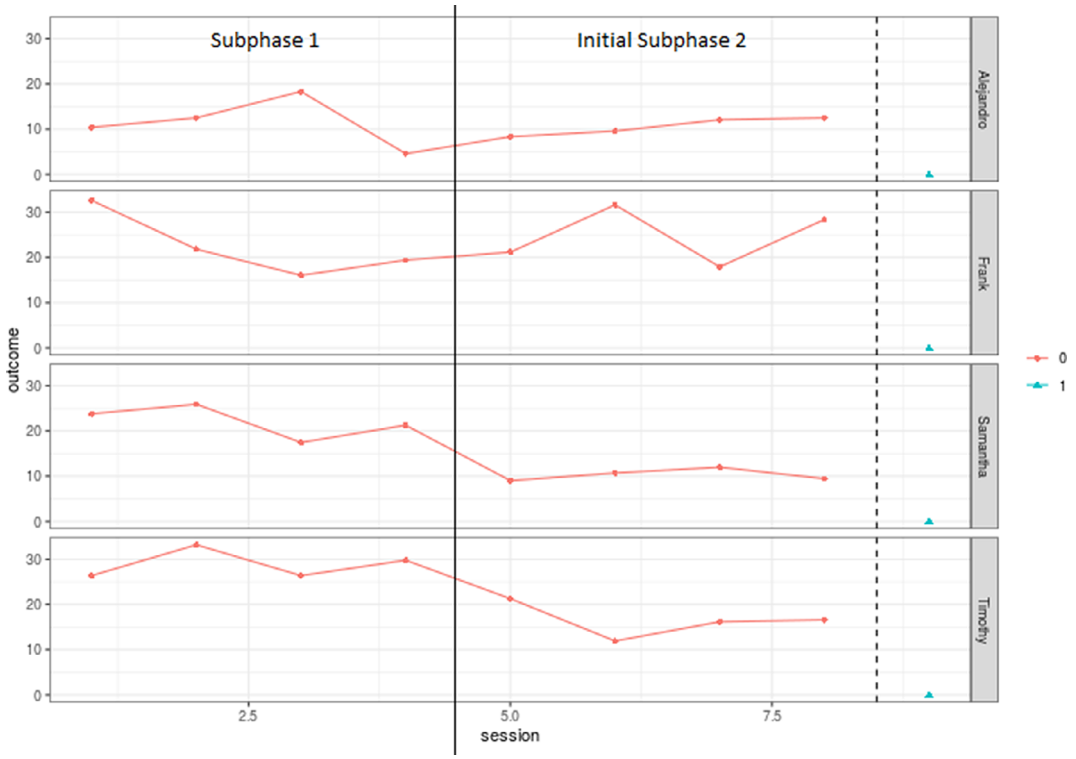


FIGURE 5 Graphical display of Subphase 1 and initial Subphase 2 data

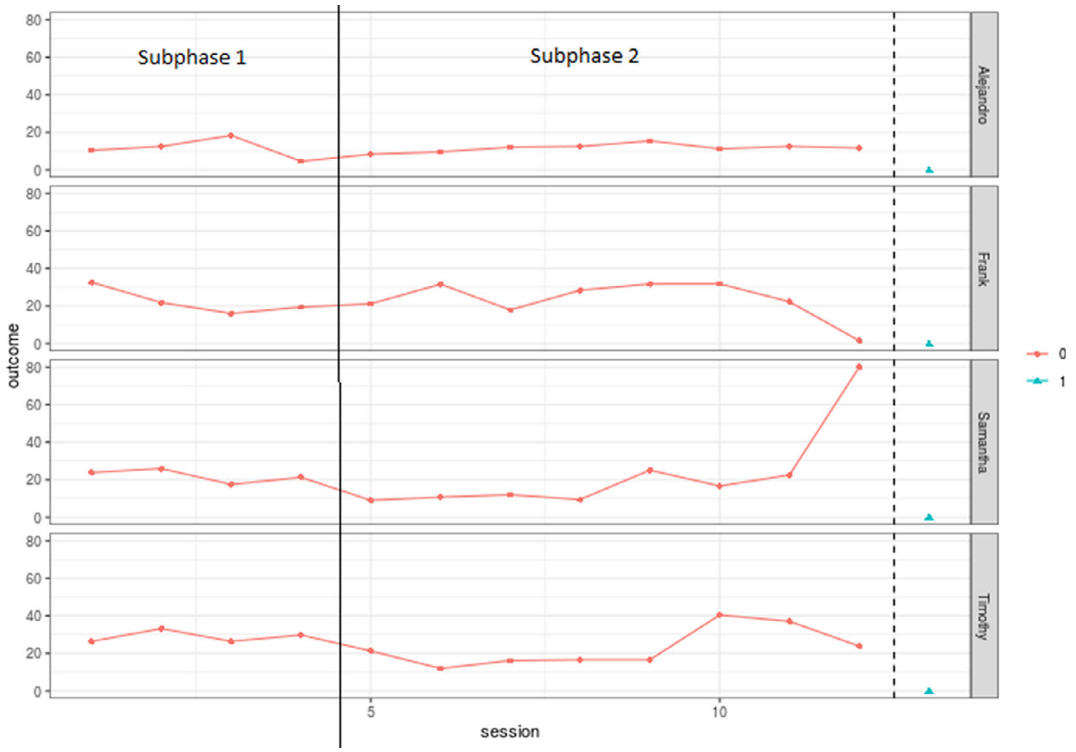


FIGURE 6 Graphical display of Subphase 1 and Subphase 2 data

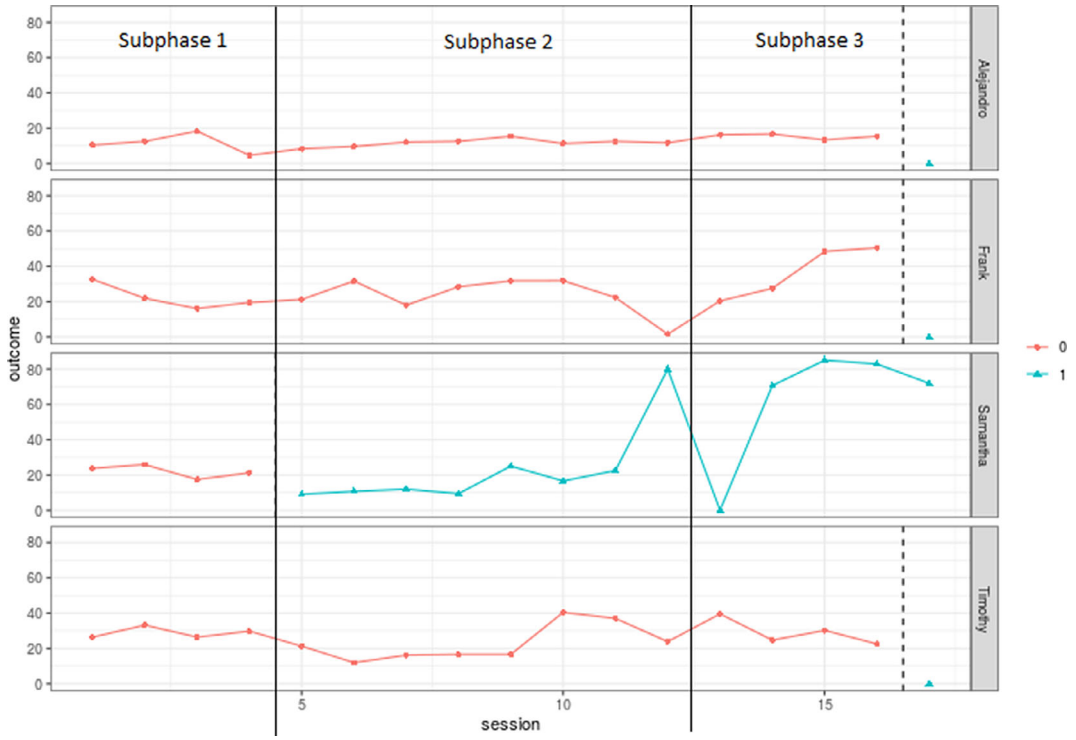


FIGURE 7 Graphical display of Subphase 1, Subphase 2, and Subphase 3

2.2.4 | Subphase 4

The interventionist started the intervention for a third participant and gathered four measures during this subphase, in which three participants were in intervention and one remained in baseline. Changes in the percentage of syllable correct are expected for one participant, whereas no changes are expected for the other participants. Figure 8 displays the data obtained during subphases 1, 2, 3, and 4 for the four participants (where Subphase 4 is part of the intervention phase for three participants and continuation of the baseline phase for one participant).

No clear changes were obvious (for Timothy or Alejandro), so one extra data point was requested by the analyst. After the fifth session in Phase 4, it was clear to the analyst that the intervention was delivered to Timothy, see Figure 9. The analyst informed the intervention team that the intervention could be started for the last participant.

2.2.5 | Subphase 5

The interventionist started the intervention for the last participants and so all gathered data are during the intervention phase. Changes in the percentage of syllable correct are expected for one participant, whereas no changes are expected for the other participants. Figure 10 displays the data obtained during all subphases for the four participants.

No clear changes were obvious, so extra data points were requested by the analyst. However, after the eighth session during Subphase 5, no clear change in the data pattern was observed for the last participant exposed to the intervention. Because of the a priori decision of a maximum of eight data points during a subphase, the experiment was ended and the last participant was assumed to be a nonresponder. All gathered data is displayed in Figure 11.

2.2.6 | Final phase—specification of the intervention sequence

During this last step of the MVA, the analysis team specifies what they believe is the sequence of participants introduced to the intervention. The intervention team indicates if they are correct. If not correct, the analysis team continues to make specifications until the correct intervention order is specified. The *p*-value is computed as: *p* = number of specifications divided by the number possible assignments. For the study of Byun et al. (2017), the analyst chose the correct order the first time, namely (1) Samantha, (2) Frank, (3) Timothy, and (4) Alejandro. The interventionist confirmed that this order was correct. As mentioned before, there were a total of 24 randomization patterns possible, given that there are four participants randomly assigned to experiments. Given that the correct randomization pattern was chosen upon the first attempt, the *p*-value is 1/24, which is .042. This indicates that there is significant evidence in support of the effectiveness of the intervention.

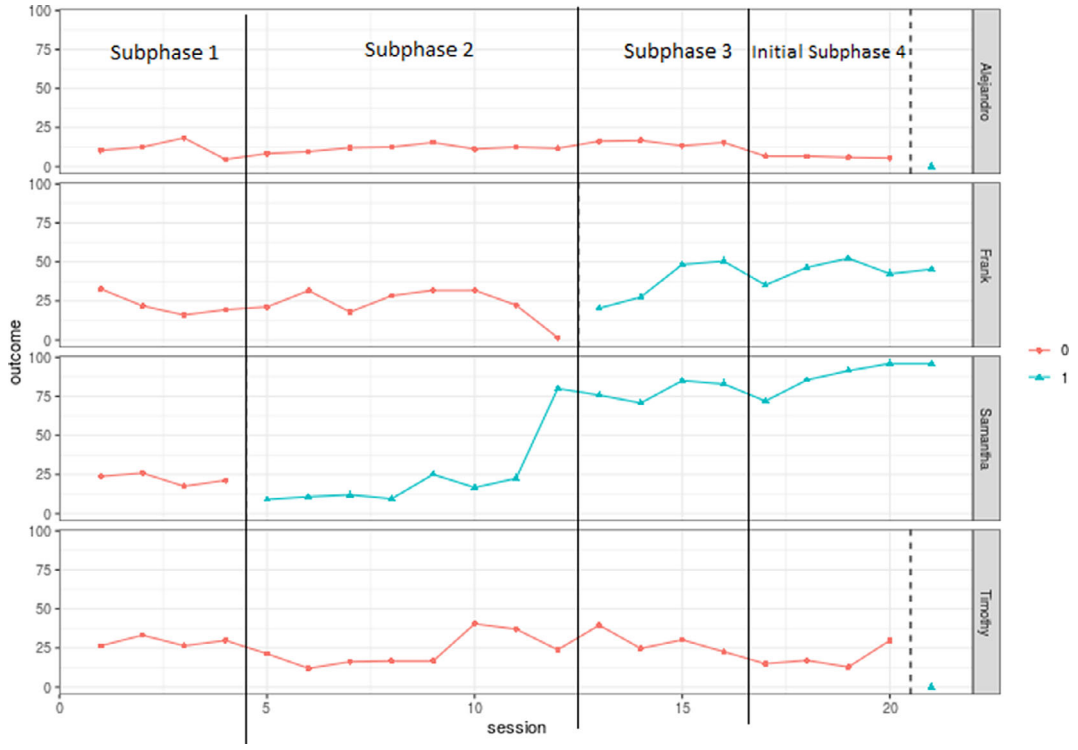


FIGURE 8 Graphical display of Subphase 1, Subphase 2, Subphase 3, and initial Subphase 4

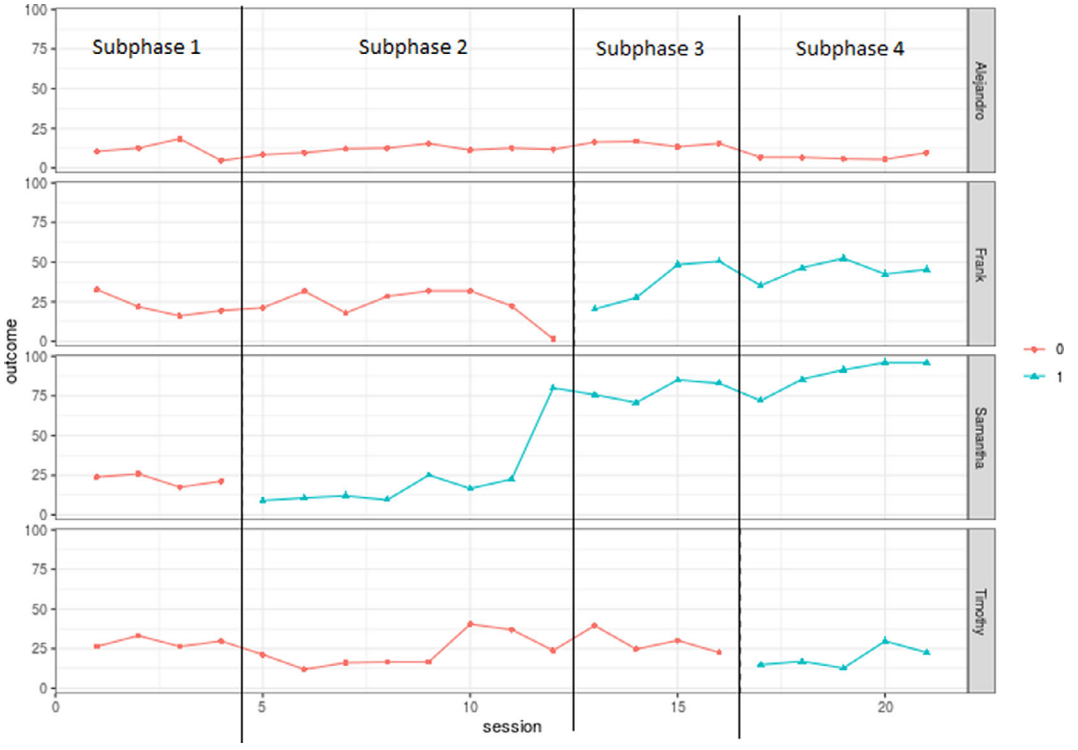


FIGURE 9 Graphical display of Subphase 1, Subphase 2, Subphase 3, and Subphase 4

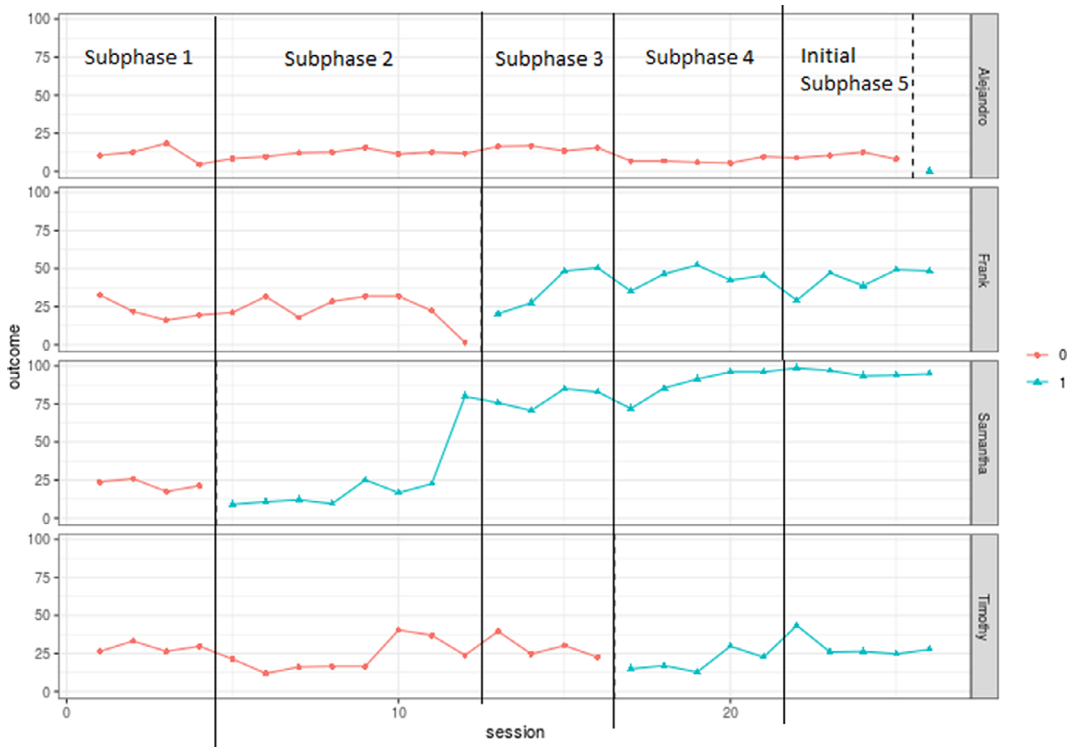


FIGURE 10 Graphical display of Subphase 1, Subphase 2, Subphase 3, Subphase 4, and Initial Subphase 5

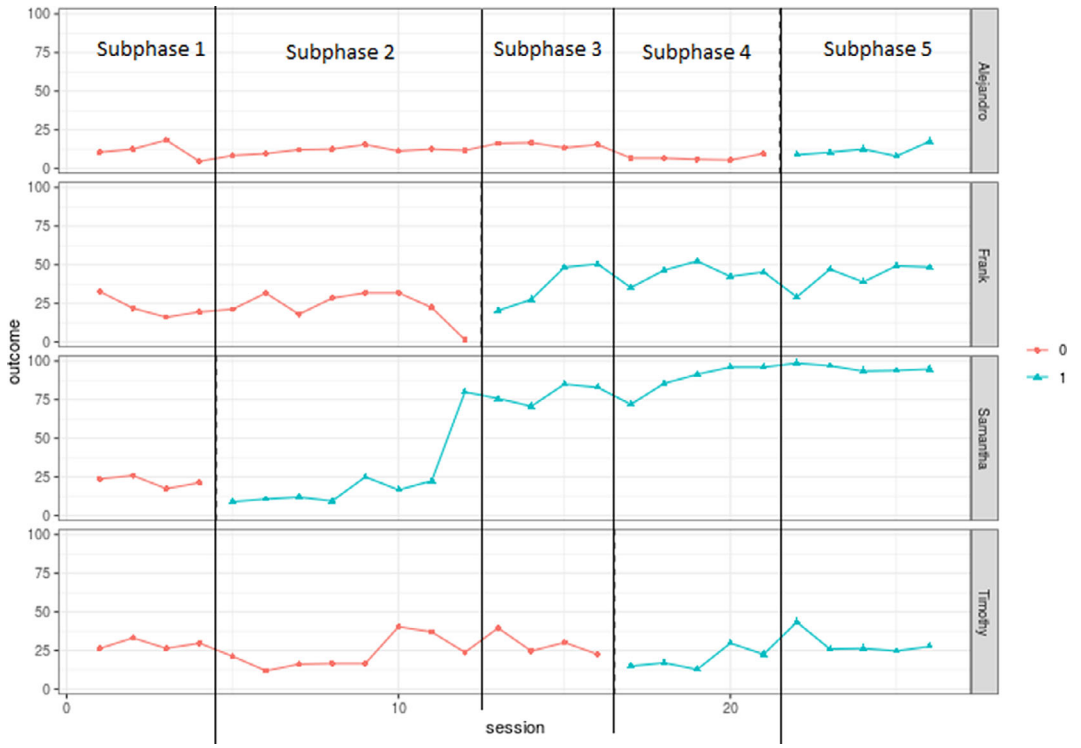


FIGURE 11 Graphical display of Subphase 1, Subphase 2, Subphase 3, Subphase 4, and Subphase 5

2.2.7 | Extension

An extension of this procedure, that enhances the reliability, is that multiple researchers are part of the analysis team. During each phase, the analysts independently chose whether more data is needed or whether the intervention can start for the next participant. If there is a discrepancy, the analysts discuss the discrepancy using the a priori agreed upon criteria (when using the mobile SCD-MVA application a chat function will be available for this purpose). In addition, at the end of the experiment, each analyst choses independently the randomization order in which the participants were exposed to the intervention independently. After this, there are two options for the analysis team to proceed. One option is that the analysts share their selected order with the team members prior to submitting this to the intervention team. If there is a discrepancy between analyst choices, a discussion among analysts can take place until agreement is reached. This option ensures reliability in the masked analysis across visual analysts. In addition, because a single order is specified, the Type 1 error rate is controlled to 1/24. The second option is that the analysts all independently make a specification and submit this to the intervention team. Only when a correct choice is made by all member of the analysis team, the choice is indicated as correct. If there is a discrepancy, the analysts need to reconsider their choice and resubmit. This approach is more stringent and thus strengthens the argument for an effect. If visual analysts are not perfectly reliable, requiring them to all get it correct would reduce the probability of a Type I error from 1/24, which makes it more impressive to get an effect, but it comes with the cost of reducing power. For more information about the MVA procedure, see Ferron & Jones (2006).

2.3 | User-friendly mobile application: SCD-MVA

In order to facilitate, enhance and help implementing the MVA approach in practice, we developed a mobile application, called SCD-MVA. The SCD-MVA application is free and currently runs on iPhones and iPads. The SCD-MVA application can be downloaded for free through the apple store and at https://www.singlecasemva.com/.

2.3.1 | Introduction to the SCD-MVA application

Given the complexity of the MVA approach, a secure, objective and user-friendly application is needed. The application enables data management and remote collaboration between practitioners, researchers, and analysts, which is welcomed given the current research climate change. In addition, details can be saved, notes can be added, and all the detailed results are made transparent. Teams do not need to meet, but can share their findings and results through the application. Later on, all the projects can be shared and previous projects can be accessed at all times by all team members. The teachers in the classroom (if they serve the role as interventionists) can immediately and virtually share the data findings with the analysis team.

The SCD-MVA application saves time as the graphs are automatically created. There is no need for the analysis team to first check emails, download the data and then make a graphical display (a skill that many applied researchers might struggle with); moreover, repeat the process for each subphase. The application sends a push notification whenever new subphase data are available (in graphical format) for the analysis team to analyze (so the analysis team members do not constantly need to check their emails). There is also an extra layer of protection as there is no conversation between analysis and intervention team. In addition, once the analysis team makes a decision, the decision is entered in the application and the intervention team receives a notification. Without the application, the approach is somewhat impractical and time consuming. For instance, if extra points need to be collected, the intervention team needs to send the extra data again to the analysis team and the analysis team needs to download that again and make the new graph. All these steps might cause significant delays in the experiment. This might also hamper future researchers to implement the MVA approach. The approach has so many advantages, but might not be easy and feasible for applied SCD researchers. This mobile application deals with this issue. Another advantage is that there can be as many team members added as needed. For instance, in the intervention team, if data collection happens by multiple members, consistency and continuity is guaranteed and data is immediately saved and shared. Otherwise this might be challenging and part of the data might be lost or tracked differently. It is also advantageous for the analysis team to have multiple members. If all the members agree unanimous to intervene, then it is clear that the a priori criteria have been met. Also, if the sequence of treatment intervention has been correctly guessed unanimously for all the participants, then one can be more certain that there is evidence in support of an intervention effect.

The SCD-MVA application will automatically create a graphical display of the data gathered and entered by the intervention team members. The graphical display will only be visible to the analysis team. The analysis team members will be able to see the created time series graphs in real time created by the data sent by the interventionist team. Depending on the criteria defined at the beginning, the analyst(s) will be able to request more data (if stability criteria are not met and no decision can be made to which participant the intervention was introduced), or ask the interventionist to start the intervention for the next participant (based on the randomized schedule that the application generated prior to the start of the experiment). An empirical demonstration of the capability and functionalities of the SCD-MVA mobile application will be provided in the next section.

2.3.2 | Step-by-step demonstration of the SCD-MVA mobile application

In this section, an overview of screenshots is provided to demonstrate the general procedure and functionality of the SCD-MVA application. Prior to creating an SCD-MVA research project, a user profile needs to be created. This only needs to be created once. Once the profile is

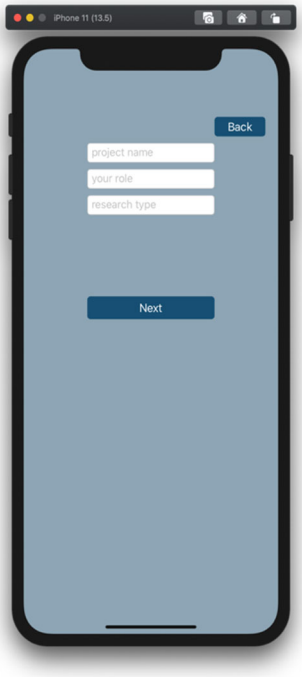
established one or multiple projects can be created. The researcher who creates the project (i.e., the research manager) first assigns itself a role (the interventionist or the analysist). Next, other researchers can be invited to be part of the research project. Screenshots providing an overview of the steps to create a SCD-MVA project are discussed first. Because members of the intervention team and members of the analysis team have different roles to fulfill, they go through different steps. The general steps (together with screenshots) for the intervention team is provided first, followed by the steps (together with screenshots) for the analysis team.

Creating an MVA project

Before the research project can start, all users create a user profile. The user profile will allow researchers to create research projects and to invite other researchers to join a research project. Below the subsequent steps are provided that need to be completed prior to the start of the SCD experiment.

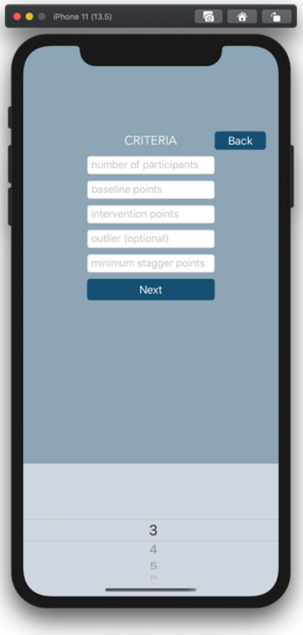
1. Create project

The research manager creates a new project. Once the research manager provides a project name and assigns itself a role (see next screenshot), he/she will be able to sign in as interventionist or analysist.



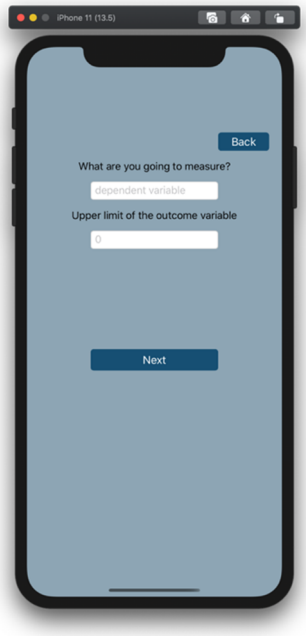
2. Assign project name, role and research type

The research manager choses a name for the project and choses his/her role (either interventionist or analyst). The research manager chooses the research design type by selecting either "response-guided" or "fixed criterion" from the drop down menu.



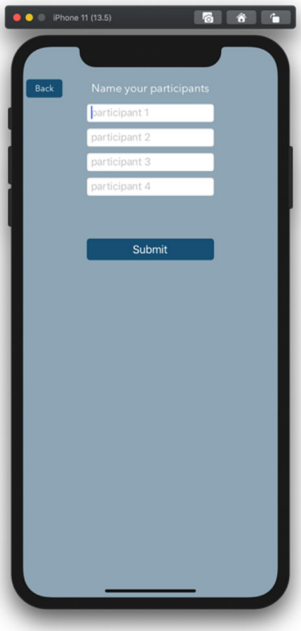
3. Specify criteria

Research parameters (criteria) are specified, namely, number of the participants in the MBD, minimum number of baseline and intervention observations, and the minimum number of observations in the stagger. The user selects the predefined parameter values from a drop-down list. For instance, the user can select three up to seven participants. Optional, the user can select criteria to identify outliers. Other criteria such as stability and the method to identify intervention effectiveness can be added as a note



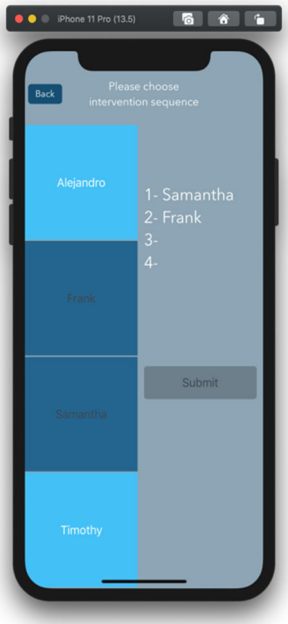
4. Define the dependent variable

The user provides a name for the dependent variable and provides the upper limit of the scale. This will be used to create the graphical display of the data and label the graphs.



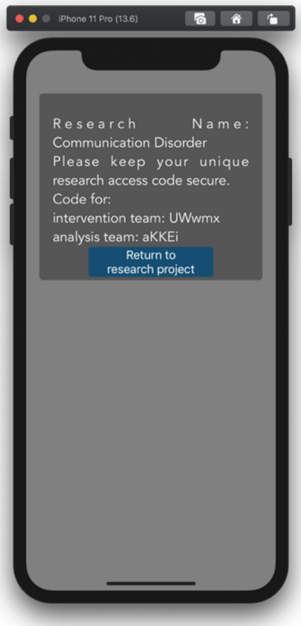
5. Name your participants

The user provides a name for the participants. This will be used to label the graphs.



7. Intervention sequence

Based on the a priori agreed upon and shared parameter decisions, the SCD-MVA application generates a random schedule that will only be visible to the intervention team members. The random schedule indicates the sequence to which the participants will be given the intervention. Alternatively, the user can define the sequence (instead of the SCD-MVA application)



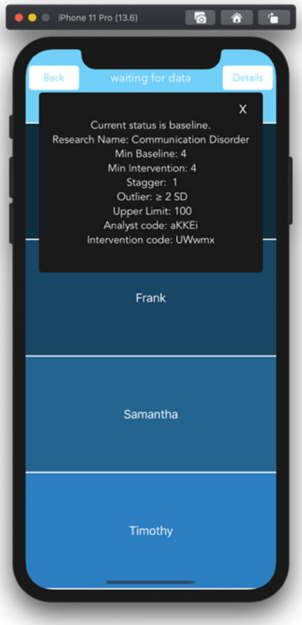
6. Share the unique research code

Once previous Steps (1–5) are completed, a unique research code (PIN) is provided by the application. The PIN is generated as two different codes; one to be shared with researchers invited to the intervention team and one for researchers invited to join the analysis team.

Researchers invited to join the project can use the PIN to sign in as interventionist or as analyst (see Screen 1 above). Once a researcher enters the PIN in the application, the research project details will pop up on the researcher's related screen. This screen will be different for members of the analysis team versus members of the intervention team.

Intervention screens

After the research project is created and researchers are signed in as interventionist or analyst, the SCD experiment can start. This section provide an overview of the subsequent screens members of the intervention team will go through during the experiment.



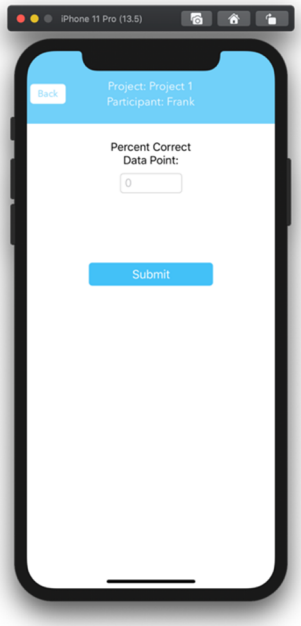
1. Overview participants

An overview of the participants is given and is available the interventionists by clicking on the "Details" button. The intervention team is reminded on the parameters and the values assigned to the parameters.

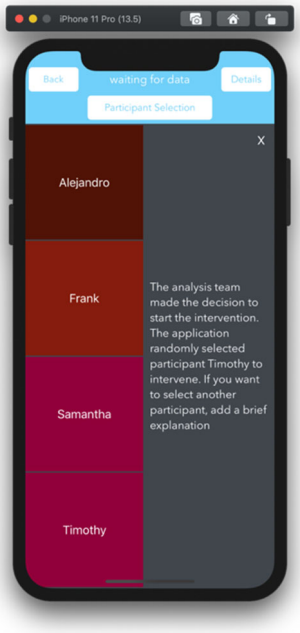
The intervention team starts collecting the data for all participants during the control condition. A minimum of four control conditions observations need to be obtained.

2. Data entering and data display

Data gathered and entered by the intervention team is displayed per participant.

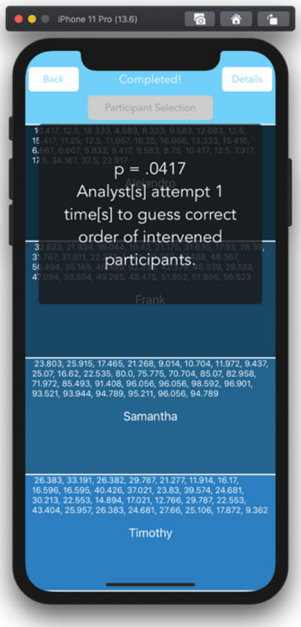


3. Here you can see how the data is entered by the intervention team. For each participant and each session, a data value is entered. Once an observation for each participant is entered, the data is automatically sent to the analysis team in graphical format. Later, when observations reach the minimum number of predefined criteria of the phase, analysts get automatically notified. This informs the analysts that data are ready to be analyzed.



4. Wait for a decision

The intervention team waits until the analysis team analyzes the data. The analysis team can decide to start the intervention for a participant or can request more data if the baseline stability criterion has not been met.

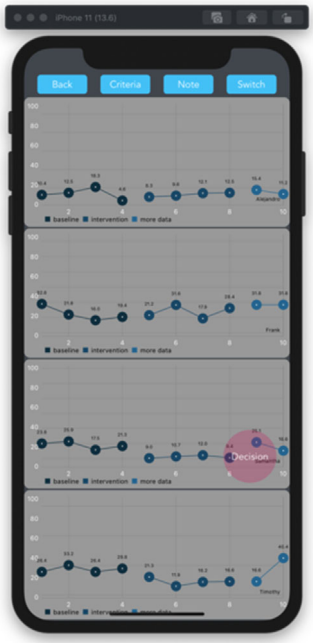


5. Results

Once all the data is gathered and analyzed by the analyst team, the intervention team received the result. Here you can see that the analysis team made a correct specification during its first attempt.

Analysis screens

After the research project is created and researchers are signed in as interventionist or analyst, the SCD experiment can start. This section provide an overview of the subsequent screens members of the analysis team will go through during the experiment.

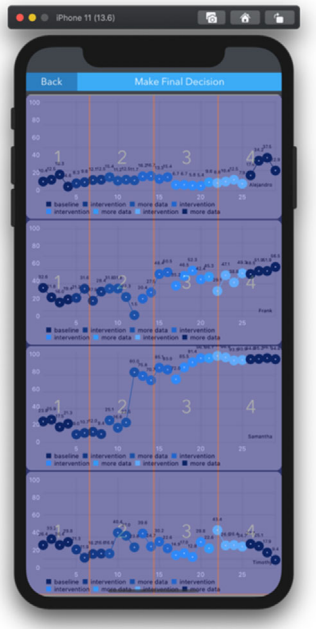


1. Graphical display

The analysis team receives the data from the interventionist team in graphical display format. Based on the analysis of the provided data, the analysis team decides whether the intervention team can start the intervention for a participant or whether more data is needed.

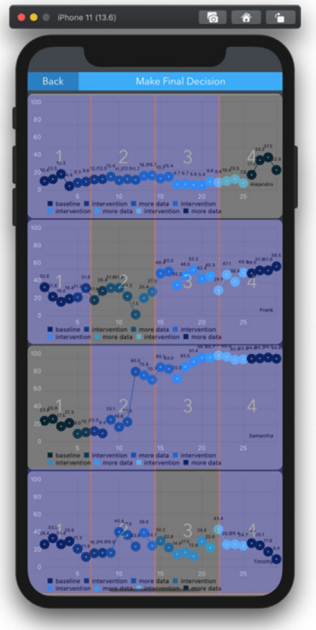
2. Decision: next phase or more data

The analysis team makes a decision by choosing “next phase” or “more data”. If more data is requested, a reason needs to be provided.

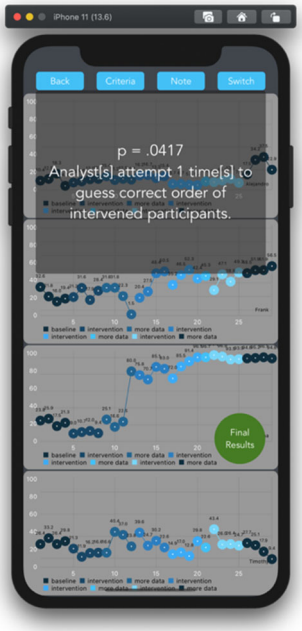


3. Final decision

At the end of the experiment, the analysis team needs to make a decision by selecting the correct intervention sequence.



The analyst team selected the order of 4 for the first participant, 2 for the second participant, 1 for the third participant, and 3 for the last participant. Once the selection has been made, the application verifies whether a correct guess has been made or whether a second attempt is needed.



4. Results final decision

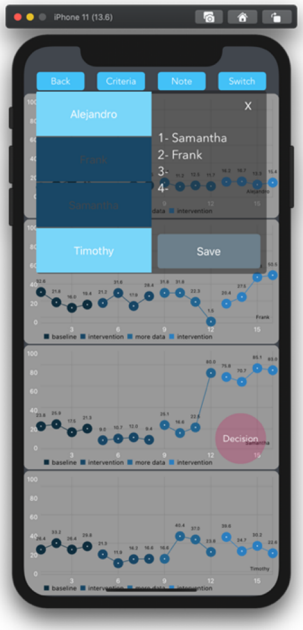
The application calculated the p-value based on the number of guesses divided by the number of random assignments possible.

Optional displays

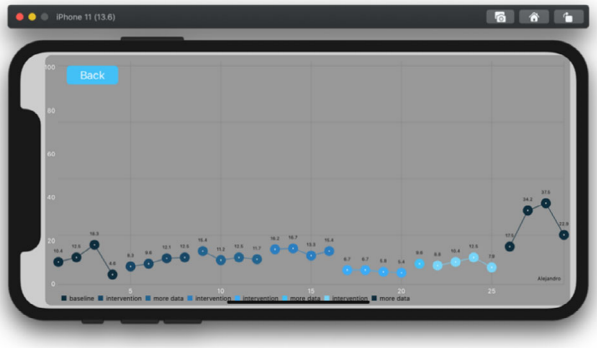
Below three options are provided to assist members of the analysis team during the process.

Optional display 1

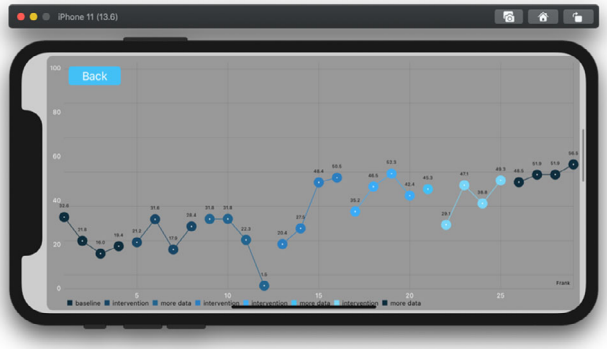
During the experiment, the analysis team can click on the criteria bottom (to have a reminder of the a priori decisions).



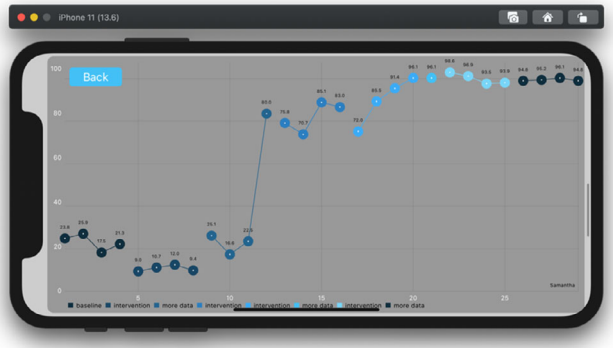
Optional display 2
During the experiment, the analysis team can make notes to use at the end of the research while making the intervention order prediction.



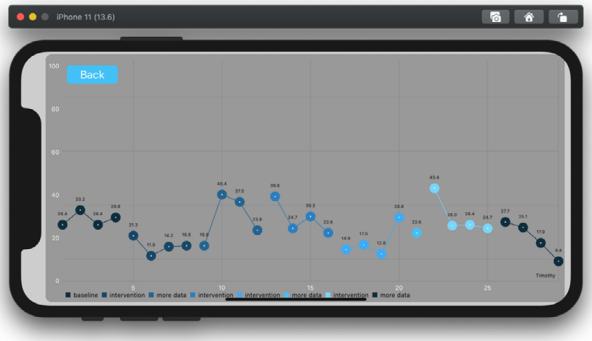
Optional display 3
Switch button clicked for Participant 1



Switch button clicked for Participant 2



Switch button clicked for Participant 3



Switch button clicked for Participant 4

3 | CONCLUSION

There is a need for research designs that are robust against disruptions caused by the COVID-19 crisis. Research designs appropriate for use in current virtual research context need to be adaptive and flexible (e.g., the length of data gathering and intervention dosage can be made responsively on changes), and allow for minimum contact between participants and between the participant and the research team. One research design that meets these new requirements is the single-case experimental design. SCDs minimize in-person contact as only a small number of participants are needed and these participants are repeatedly measured in their natural setting. This implies that there are no in-person interactions between participants. The in-person interaction between the participant and the SCD researcher is limited and video recording techniques can be used. In addition, no comparison group is needed, which is challenging to establish in a remote environment.

Among the many different SCD types, the multiple-baseline across participants design is recommended because of the high internal (i.e., staggered introduction of the intervention) and external validity (i.e., multiple participants are involved). To further enhance the internal validity and control for type I errors, randomization and response-guided experimentation are two recommended design and analysis components. These components are embedded in the MVA approach. Therefore, this article focused on the implementation of a multiple-baseline designs experiment using the MVA approach. In order to facilitate the implementation in a virtual research context, we developed a user-friendly mobile application, called "SCD-MVA." The SCD-MVA application is free and currently runs on iPhones and iPads. The SCD-MVA application can be downloaded through the apple store and at https://www.singlecasemva.com/.

The SCD-MVA mobile application has the potential to enhance the methodology to design, gather and analyze time series data by offering the following functionalities (1) creating in real time graphs, (2) avoiding errors in data transfer from intervention team to analysis team, (3) making the MVA process standardized and ensuring the masked component, (4) helping applied researchers implementing a randomized experiment, (5) assisting in making inferences and understanding the masked visual procedure, (6) helping applied researchers making causal inferences and calculating p-values, (7) facilitating data sharing and communication with other research teams, and (8) ensuring data security. Another major advantage of using this application is that it offers all these functionalities with no need for in-person meetings of the research team. All extensive planning (traditionally done in person) when designing and conducting an experiment, and analyzing the data afterward can be done and captured remotely through the mobile application.

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CONFLICT OF INTEREST

The authors do not have known conflict of interest to disclose.

PEER REVIEW

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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